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Measuring the Effects of Augmented Visualizations through Eye Gaze Tracking

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14. ABSTRACT
Eye gaze tracking is the process of tracing and measuring the motion of the eye relative to the head (i.e., the direction in which one is looking). Eye gaze tracking is a common technique used to objectively measure a user's attention and responses to information presented to them. In particular, we believe that eye gaze tracking can be used to gauge the effectiveness of different visualization styles that have been augmented to support analyst decision making. However, assisting the analyst in connecting with augmented visualizations can be challenging if the information is not presented in a clear and concise way. An empirical study that seeks a correlation between visual augmentation style and decision effectiveness will produce insights into the factors that affect the task. These insights will lead to techniques that help analysts filter vast amounts of information so that they can make informed decisions about critical matters in a timely fashion. This study proposes to use eye gaze tracking techniques to measure whether link line thickness can be used to visually increase situational awareness, thus allowing analysts to make decisions more rapidly.

15. SUBJECT TERMS
eye tracking, gaze patterns, value of information, visual analytics, link-node diagram, human computer interaction

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1. Introduction

The process of determining information usefulness in an efficient manner is crucial in settings with high-velocity information exchange such as hospital trauma, stock exchanges, or battlefield mission control. Decision makers often overlook valuable information because such a large volume is being presented. In these situations, it is useful to understand the optimum levels of information that users can process without experiencing cognitive overload. Cognitive overload has been widely studied in the literature[1–3] and refers to a state where the user is taking in more information than they can process efficiently.[4] To study this condition more closely, the US Army Research Laboratory (ARL) has created a visual analytic tool for increasing situational awareness. This tool, which combines nodes with connecting links to create a network of associated nodes,[5] has been used in multiple fields for criminal investigation (fraud detection, counterterrorism, and intelligence), computer security analysis, search engine optimization, market research, medical research, and art.[6] Specifically, ARL is interested in using it for military intelligence and social network analysis.[7] The links are overloaded in ARL's version to convey the value of the information defining the link. The visual method of overloading is done by varying the link thickness according to value such that a thicker link represents information with a higher value.

1.1 Value of Information

The value of information (VoI) is a metric that computes a likelihood of applicability based on metadata of recorded information. Specifically, VoI combines source reliability, likelihood that data are true, and timeliness with respect to mission.[8,9]

1.2 Eye Gaze Tracking

Eye gaze tracking has been widely used in studies that analyze how humans process visual information displays.[10] Software can be used to capture and quantify a person's attention and focus, helping researchers to understand user interactions and provide awareness of visual stimuli. Consequently, we can determine which parameters drive situational awareness.

1.3 Study Background

This study aimed to use eye gaze tracking data to identify parameters contributing to the findings from our previous crowdsourcing visual analytic experiment.[11] In that experiment, users were tasked to select the most important node in a link-node diagram. Some users viewed a classic link-node diagram, while others viewed a VoI-enhanced link-node diagram in which the thickness of the links was varied to convey value. The ultimate goal was to demonstrate that the VoI-enhanced link-node diagrams would significantly improve the analyst's situational awareness, while also reducing their mental burden, allowing them to make the best decision in the least amount of time.

While the experiment did bear out some notable differences, it was impossible to determine significance due to small sample size. To explore this phenomena further, ARL and Towson University collaborated to re-create the experiment with the caveat that participants would wear eye gaze tracking hardware. The hypothesis was that the eye gaze tracking results would reveal differences in focus and strategy that clarify the cause of the significant differences in results between the overloaded and normal diagram.

2. Methods

2.1 Human Subjects

This study falls under the ARL internal review board (IRB) Exempt Research Determination for Protocol (ARL 18-014), which indicates that it is exempt from regulation 32 CFR 219. This is because the data that ARL gathered from Towson University were not identifiable information. In addition, ARL 1) was neither involved nor interacted with human subjects, 2) provided no temporary services, and 3) was not part of the research personnel. Towson University's IRB found the research to be exempt (14-X145) from general Human Participants requirements according to 45 CFR 46.101(b)(2), as well.

2.2 Experimental Setup

To investigate the effectiveness of its visual analytic tool, ARL researchers conducted a crowdsourcing experiment where participants were asked to identify the most important node in a link-node diagram.[11] Collaborators from Towson University's Department of Computer and Information Science in Baltimore, Maryland, recruited 17 computer science students for participation in this experiment. Participants were recruited via online solicitation and word of mouth, as well as through flyers posted in common areas and distributed in approved classrooms (i.e., those in which distribution was approved by a faculty member). All flyers were approved by Towson University's IRB prior to posting. Participants were not compensated for their time. Data collection took place in a usability laboratory at a time mutually agreed upon by data collectors and participants. The

IRB briefed participants about the study and its possible effects. Upon consent, each participant received a demographic survey, with questions that included occupation, age, gender, primary language, education level, hours spent on the computer daily, and data visualization experience. Participants were then directed to the Tobii Pro Studio information visualization software, which they were required to use to calibrate the eye gaze tracking device. During the calibration procedure, the participant was asked to gaze at different points on the monitor. After the participant calibrated the eye gaze tracking device and gained and familiarity with the interface, they were asked to use the ARL visual analytic tool to answer a series of questions pertaining to the different link-node visualizations displayed in the interface from the VolunteerScience.com website. The participant answered these questions while using the eye gaze tracking device. After the experiment was complete, the participant was presented with a post-experiment survey. User bias was minimized by allowing subjects to participate in the study only one time.

Qualified subjects were presented with a sample graph for practice purposes and a set of instructions directing them to imagine themselves as analysts studying a link-node diagram. The instructions went on to specify that each link incident upon a node represents the metric to be maximized, with a thicker line representing a more relevant node (Fig. 1). Subjects were required to do the following:

1) Assess the diagram to discern the node with the greatest degree centrality, which was modulated by line thickness in the VoI cases.

2) Highlight the node via mouse click to indicate that a selection has been made. (The selected node was also displayed in a list next to the diagram.)

3) If unhappy with the selection, press the Reset button to restart the selection process.

4) Once happy with the selection, press the Submit button to record the answer.

5) Drag the nodes and manipulate the graph to optimally assess the degree centrality.

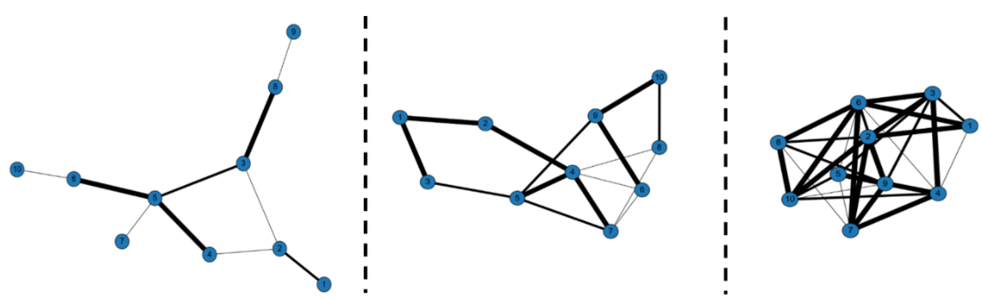

Fig. 1 Link-node diagrams from experiment showing 22% (left), 33% (center), and 66% (right) VoI enhancement

We hypothesized a significant difference in the accuracy and decision time between participants viewing the value-overloaded diagrams and those viewing the normal diagram.

2.3 Data Analysis Methods

Eye gaze tracking data were collected using Tobii Pro Studio information visualization software. This software collects a large number of attributes for an eye gaze tracking experiment (the x gaze position, y gaze position, and associated timestamp are critical for this study) and it uses the Velocity–Threshold Identification (I-VT) Fixation Filter to classify each gaze point as a fixation, saccade, or unclassified.[12] Fixations are areas in a scene in which gaze points are clustered in space and time, and saccades are gaze points that indicate movements between fixations. The I-VT Fixation Filter uses the measure of angular velocity to classify fixations and saccades, where gaze points below a certain angular velocity are classified as fixations and gaze points above that threshold are classified as saccades. An angular velocity threshold of 30°/s was used in this experiment.

Fixation duration measures the length of time that a subject spends examining a particular object and can indicate the extent of visual processing needed to interpret a scene (for example, fixation duration might signify the length of time typically spent looking at a particular node or graph edge). In this study, the maximum fixation duration indicates the greatest length of time spent looking at a region of the screen.

Saccadic amplitude measures the angular distance the eye travels during a saccadic eye movement. A smaller saccadic amplitude intuitively signifies that a user's eye moved a shorter distance across a visual stimuli before making a decision. In this study, saccadic amplitude is used to gauge how much eye movement is needed to select the correct node in the graph.

This study explores maximum fixation duration and saccadic amplitude as they relate to the following:

1) whether or not participants selected the most important node in the graph
2) each of the graphs examined by the participants
3) each of the 17 study participants
4) selection strategy
5) line thickness
6) VoI enhancement

2.4 Conditions

To keep the experiment consistent across all conditions, the number of nodes (10) was kept constant and the number of links were varied by the graph density equation (Eq. 1). This experiment included six conditions: 22%-VoI, 22%-Ctrl, 33%-VoI, 33%-Ctrl, 66%-VoI, and 66%-Ctrl. The graph density formula calculates the density of the graph given a set of nodes and edges. The graph density formula is

$$D = \frac{2 \times E}{N(N-1)}, \tag{1}$$

where D is the density of the graph, E is the number of edges in the graph, and N is the number of nodes in the graph (N is 10 for all graphs). In this experiment, the density was 22% (10 edges), 33% (15 edges), and 66% (30 edges). The initial density levels were determined by a perceived level of difficulty.

3. Results

This section presents the eye gaze tracking data analysis. Boxplots show the statistical distribution of maximum fixation duration and mean saccadic amplitude relative to the categorical variables specified in Section 2.3.

3.1 Maximum Fixation Duration

The boxplots provided in Fig. 2 show distribution of maximum fixation duration as it relates to different categorical variables. Figure 2.1 is the boxplot for maximum fixation duration as it relates to whether or not the participant selected the correct node. This boxplot shows similar mean and median maximum fixation durations for participants who selected both the correct and incorrect node. However, the maximum fixation duration for participants who selected the correct node is more variable than for those who did not. Both distributions show a few participants with abnormally high maximum fixation durations.

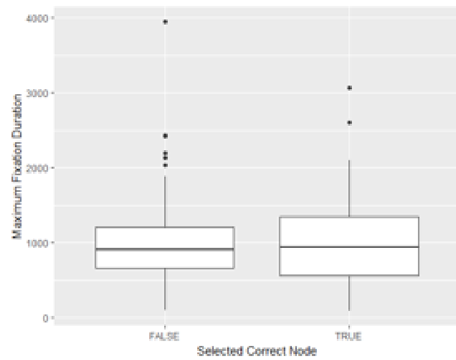

Figure 2.1. Boxplot of Maximum Fixation Duration and Selection of Correct Node

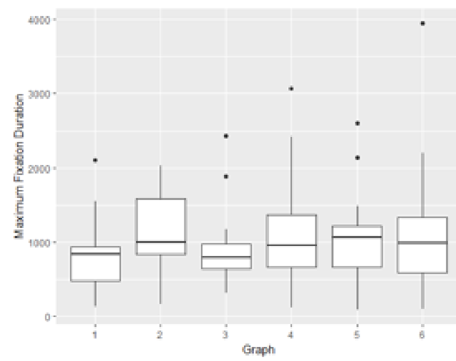

Figure 2.2 Boxplot of Maximum Fixation Duration and Graph

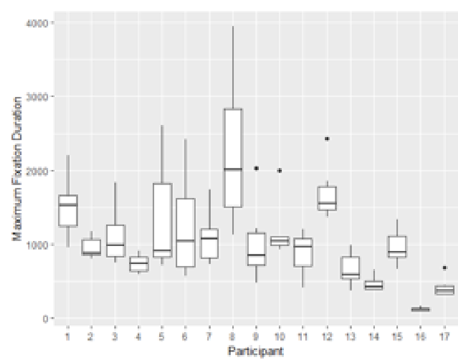

Figure 2.3 Boxplot of Maximum Fixation Duration and Participant

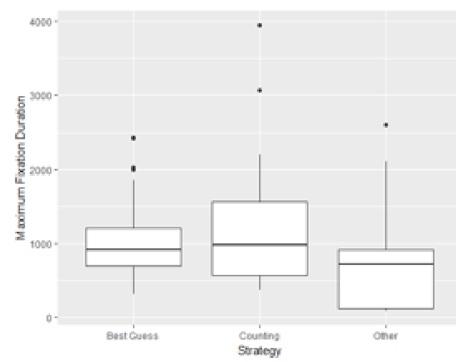

Figure 2.4 Boxplot of Maximum Fixation Duration and Strategy

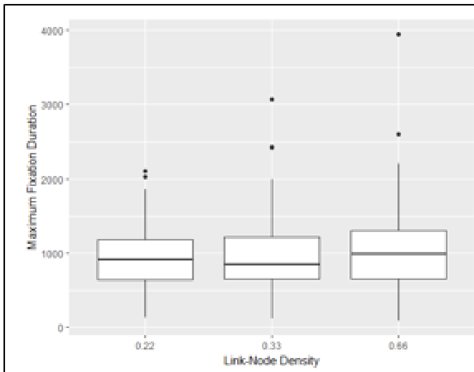

Figure 2.5 Boxplot of Maximum Fixation Duration and Link-Node Density

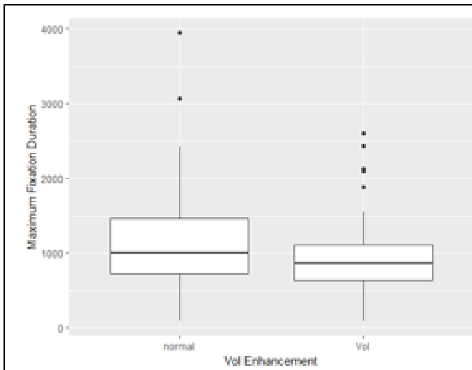

Figure 2.6 Boxplot of Maximum Fixation Duration and VoI Enhancement

Fig. 2 Boxplots of maximum fixation duration relative to categorical variables

Figure 2.2 is the boxplot for maximum fixation duration as it relates to each of the graphs examined by the participants. This boxplot shows that, overall, graphs 1 and 2 have the lowest maximum fixation rate across all participants. Graph 2 has a notably higher maximum fixation duration than graph 1, and the graph 2 has a median maximum fixation duration similar to graphs 4, 5, and 6. Graphs 2, 4, and

6 have wider ranges of maximum fixation duration across all participants and all but graph 2 have outliers at higher levels. As it relates to the task, participants generally had lower dwell times on the most salient feature in graphs 1 and 3.

Figure 2.3 is a boxplot for maximum fixation duration as it relates to each study participant. This boxplot shows notable differences between the maximum fixation duration for each participant. For example, participant 8 demonstrated greater and more variable maximum fixation durations for each graph than the other participants. This participant used the counting strategy and though given a line thickness of 4, selected the correct node in only two of the six graphs, indicating that they experienced difficulty performing some of the tasks.

Conversely, participant 16 had very low maximum fixation durations and selected the correct node three out of six times. Even more confounding is the fact that participants 7 and 11 had a somewhat similar maximum fixation duration distribution, but while participant 7 selected the correct node all six times, participant 11 never selected the correct node.

Figure 2.4 is a boxplot of maximum fixation duration as it relates to selection strategy. This boxplot shows some notable differences between each strategy—the maximum fixation duration for participants who used best guess varied much less than for those who used counting. Participants who classified their strategy as other had much smaller maximum fixation durations than those who used the best guess and counting strategies.

Figure 2.5 is a boxplot of maximum fixation duration as it relates to link-node density. This boxplot shows that the maximum fixation duration for link-node density is somewhat higher at the 66% value. This suggests that graphs with higher link-node densities require more visual processing time.

Figure 2.6 is a boxplot of maximum fixation duration as it relates to VoI enhancement. This boxplot shows that in general, enhancing VoI reduces maximum fixation duration. In other words, incorporating VoI in the graph can reduce the time that it takes for an analyst to select the most influential node.

3.2 Mean Saccadic Amplitude

The boxplots provided in Fig. 3 show distribution of mean saccadic amplitude as it relates to different categorical variables. Figure 3.1 is the boxplot for mean saccadic amplitude as it relates to whether or not the participant selected the correct node. There is a slight difference in the results, showing that participants who entered the correct node had slightly higher mean saccadic amplitudes and the distribution is positively skewed.

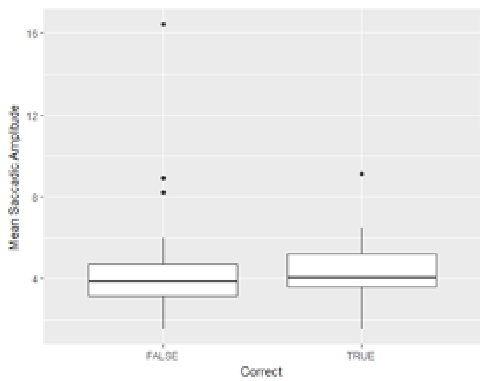

Figure 3.1. Boxplot of Mean Saccadic Amplitude and Selection of Correct Node

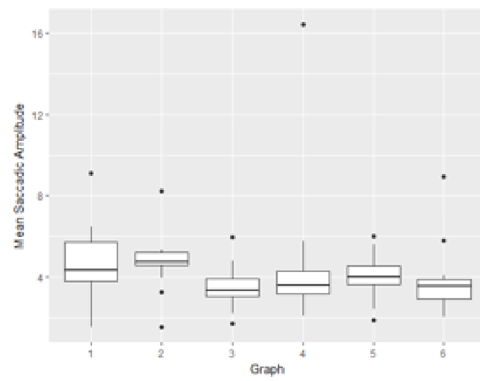

Figure 3.2 Boxplot of Mean Saccadic Amplitude and Graph

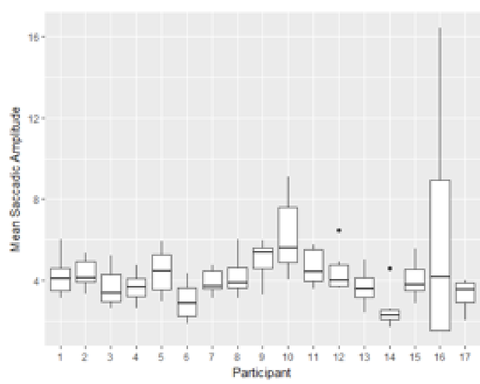

Figure 3.3 Boxplot of Mean Saccadic Amplitude and Participant

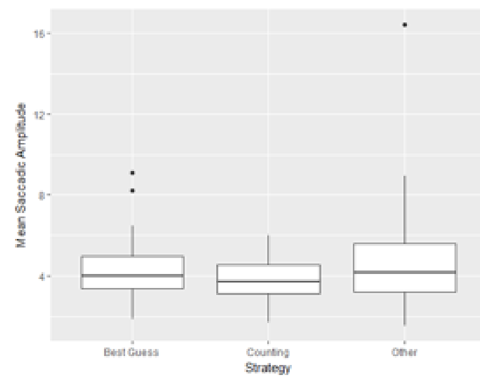

Figure 3.4 Boxplot of Mean Saccadic Amplitude and Strategy

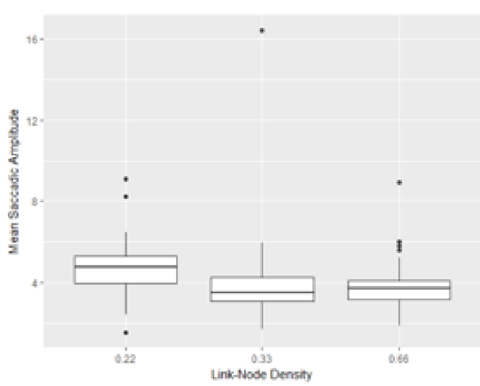

Figure 3.5 Boxplot of Mean Saccade Amplitude and Link-Node Density

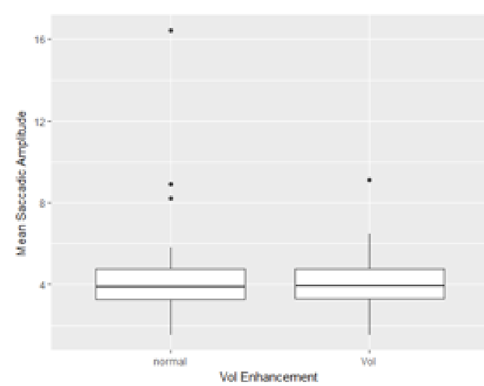

Figure 3.6 Boxplot of Mean Saccade Amplitude and VoI Enhancement

Fig. 3 Boxplots of mean saccadic amplitude relative to categorical variables

Figure 3.2 is a boxplot for mean saccadic amplitude as it relates to each of the graphs examined by the participants. There are slight differences across the graphs—graph 1 has the highest variability in mean saccadic amplitude and the median value of graph 2 is slightly higher than the others (but it also has the lowest variability). Overall, the pattern of mean saccadic amplitude as it relates to each of the graphs might be influenced by factors such as the graph's physical layout and the distance between important nodes.

Figure 3.3 is a boxplot for mean saccadic amplitude as it relates to each study participant. This boxplot shows notable individual differences in saccade amplitude. For example, participant 16 has a wide range of mean saccadic amplitude across all tests, with a median that is within the range of other participants. This indicates that participant 16 may have had some difficulty visually processing some of the graphs. Conversely, participant 14 has a consistently low mean saccadic amplitude. Overall, this boxplot highlights major differences between participants with respect to how they visually process link-node diagrams.

Figure 3.4 is a boxplot of mean saccadic amplitude as it relates to selection strategy. The counting strategy has a slightly lower mean saccadic amplitude than the best guess and other strategies. This could indicate fewer eye movements from participants who used the counting strategy because they likely went from node to node to count how many edges go into each node.

Figure 3.5 is a boxplot of mean saccadic amplitude as it relates to link-node density. This boxplot suggests that the mean saccadic amplitude decreases as the link-node density increases. This is intuitive, since higher density graphs require fewer eye movements to investigate each node.

Figure 3.6 is a boxplot of mean saccadic amplitude as it relates to VoI enhancement. This boxplot shows no clear difference between the two conditions, indicating that VoI is a lesser factor in saccadic movements.

4. Discussion and Conclusion

This eye gaze tracking study did not reveal any notable fixation differences when graph attributes (density, normal, or overloaded links) were modified, which does not allow us to conclude any cause for the crowdsourcing results. On the contrary, there were notable differences in the fixation times per individual user (see Fig. 2.3). Combined with a low user count (17), the inconsistent performance of the users may have obscured notable differences due to modifying the graphs.

Future studies will place greater emphasis on participant training in an effort to reduce the variance in performance, thereby decreasing noise and enabling more meaningful results. In addition, a wider variety of visual representations such as color, line type, or a combination will be considered to better denote the VoI.

5. References

1. Miller GA. The magical number seven, plus or minus two: some limits on our capacity for processing information. Psychol Rev. 1956;63(2):81–87.

2. Denenberg DA, Hansen L, Czarnota N, Chakraborty J, Norcio A. The effects of color and layering on comprehension of multi-layered email messages. In: 11th International Conference on Human-Computer Interaction; 2005 July 22–27; Las Vegas, NV.

3. Chakraborty J, McGuire MP. Directional scan path characterization of eye tracking sequences: a multi-scale approach. In: 2016 Future Technologies Conference (FTC); 2016 Dec 6–7; San Francisco, CA. doi:10.1109/FTC.2016.7821589.

4. Chakraborty J, McGuire MP, Pandey G. Preliminary findings from an information foraging behavioural study using eye tracking. In: Langdon P, Lazar J, Heylighen A, Dong H, editors. Designing around people. Springer, Cham; 2016. p. 259–268. doi: 10.1007/978-3-319-29498-8_27.

5. Holten D, Van Wijk JJ. A user study on visualizing directed edges in graphs. In: CHI 2009. In: Proceedings of the 27th International Conference on Human Factors in Computing Systems. 2009 Apr 4–9; Boston, MA. c2009. p. 2299–2308.

6. Link analysis. Wikipedia; 2017 Oct 30 [accessed 2018 July 25]. https://en.wikipedia.org/wiki/Link_analysis.

7. Mittrick M, Richardson J, Vertlieb A, Hanratty T. Developing a value of information (VoI)-enabled system from collection to analysis. Aberdeen Proving Ground (MD); Army Research Laboratory (US); 2016 Nov. Report No.: ARL-TN-0797.

8. Hanratty T, Hammell RJ, Heilman E. A fuzzy-based approach to the value of information in complex military environments. In: Benferhat S, Grant J, editors. Lecture notes in computer science. Vol 6929. Berlin, Heidelberg (Germany): Springer; 2011. p. 539–546.

9. Hanratty TP, Newcomb EA, Hammell RJ 2nd, Richardson JT, Mittrick MR. A fuzzy-based approach to support decision making in complex military environments. Int J Intell Inf Technol. 2016;12(1):1–30.

10. Duchowski A. Eye tracking methodology: theory and practice. 2nd ed. London (UK): Springer–Verlag London Ltd.; 2007.

11. Mittrick M, Richardson J, Asher DE, James A, Hanratty T. A visualization technique to improve situational awareness. Proc SPIE, Next-Generation Analyst VI. 2018 Apr 27;10653:106530L. doi: 10.1117 /12.2304280. https://doi.org/10.1117/12.2304280.

12. Komogortsev OV, Gobert DV, Jayarathna S, Koh DH, Gowda SM. Standardization of automated analyses of oculomotor fixation and saccadic behaviors. EEE Trans Biomed Eng. 2010;57(11):2635–2645.

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